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Advertising and food, drink and tobacco consumption in the United Kingdom: a dynamic demand system

Martyn Duffy*

Institute of Science and Technology, Manchester School of Management, University of Manchester, P.O. Box 88, Manchester, M60 1QD, UK

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Abstract

This paper tests for the influence of advertising on the inter-product distribution of consumer demand for non-durable goods and services in the UK, 1963–1996. The long-run demand for seven categories of non-durable products is modelled through an advertising-augmented version of the almost ideal demand system (AIDS), which is incorporated into an error-correction model to allow for short-run dynamic adjustments to long-run equilibrium positions. Model estimates confirm that the restrictions of price homogeneity and symmetry appear to be consistent with the data, yield measures of the various types of demand elasticity that are in general plausible, confirm the strong influence of prices on the allocation of consumer expenditure, but find little evidence to support the hypothesis that advertising has the power to effect marked changes in the inter-product pattern of consumer demand in the UK.

JEL classification: C3; D12; I18; M3

Keywords: Advertising; Error-correction models; Demand system

1. Introduction

Economists and commentators have long debated the influence of advertising on the pattern of consumption across broad product categories. Many have expressed concern about the adverse effects upon consumer health and welfare that are likely to occur when advertising encourages higher levels of consumption of certain products. Food, drink and tobacco advertising have received most of this critical attention, leading to campaigns, often successful, in many countries to restrict or even prohibit some or all types of advertising for these products. The aims of advertising restrictions in these markets include the reduction of the incidence of smoking, the minimisation of alcohol-related illnesses, accidents and rates of absenteeism from work and an improvement in the nation's diet by limiting the promotion of 'unhealthy' foods.

The aim of this paper is to inform this debate by assessing the potency of advertising effects for these products through the econometric estimation of an augmented version of an almost ideal demand systems (AIDSs) for non-durables consumption in the UK. A system-wide approach to demand analysis is the most appropriate framework for examining a system-wide phenomenon such as the effect of advertising upon the inter-product distribution of demand. An advertising-augmented demand system for seven product groups is estimated in this paper. The seven

* Tel.: +44-161-200-2483; fax: +44-161-200-3505.
E-mail address: m.duffy@umist.ac.uk (M. Duffy).

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groups are: (1) beer; (2) spirits; (3) wine; (4) tobacco; (5) food and soft drink; (6) clothing and footwear; (7) other non-durables.

Reflecting recent developments in the unit roots and econometrics literature, careful attention is paid to the time series properties of the data, and a vector-autoregressive, distributed lag approach is employed in modelling the dynamic consumer behaviour. The general approach followed is conditioned on the view that there may exist a long-run 'equilibrium' cointegrating demand system which is worth identifying and estimating for it would provide an appropriate basis for testing the long-run effects of advertising and, indeed, other variables on the demand for food, drink, tobacco and other goods.

It is also important, however, that the model specification allows for short-run adjustments towards the long-run equilibrium. The process of adjustment may be incomplete in any single period of time because of inertia caused by strongly habitual consumption, adjustment costs and imperfect information and uncertainty. In the period before these adjustments are completed, consumers will be 'out of equilibrium' and their short-run responses to changes in prices, advertising and income may be little guide as to their long-run effects. For the same reason, the restrictions on optimising or 'equilibrium' consumer behaviour that are suggested by classical demand theory, such as price homogeneity and symmetry, need not be satisfied in the short-run, although they may be consistent with long-run behaviour.

In order to meet all of the above requirements (the representation and estimation of long-run preference parameters in a cointegrating, AIDS and the separation of short-run from long-run behaviour) this paper employs the dynamic error-correction specification of Anderson and Blundell (1982, 1983, 1984). This approach can be interpreted as one that exploits the well-known connection between cointegrated time series and their error-correction representation. In the Anderson and Blundell formulation, however, the error-correction model is expressed in terms of deviations from a long-run position that is described by an AIDS.

In this paper the Anderson–Blundell approach to the estimation of long-run relationships is preferred to the popular Johansen (1988) reduced rank regression technique, for it uses economic theory (demand system analysis) from the outset to help determine the likely rank of the cointegration space and to identify the long-run structural relations, including the division of variables into endogenous and exogenous categories. The long-run structural relations can then be recovered from estimates of the error-correction model and finally the cointegration properties of the system may be checked. In contrast, the Johansen approach reverses this sequence by starting with the assumption that all variables (apart from those that are clearly deterministic, such as constants, linear trends and dummy variables) are potentially endogenous; then testing for the rank of the cointegration space; next using exactly and over-identifying restrictions to estimate meaningful structural relations; and testing for weak exogeneity. Some economists have described the Johansen approach as being too atheoretical, because it concentrates too much on statistical properties and makes little use of economic theory, at least in the early stages of the specification and estimation of a model (Pesaran, 1997).

The structure of the paper is as follows. The next section describes the static (long-run) and dynamic (short-run) models of demand that are used in this study. Section 3 contains a description of the data, sources and methods, together with an examination of the time series properties of the variables. A report and discussion of the empirical results is presented in Section 4. The paper closes with some conclusions in Section 5.

2. Model specification

2.1. The static model

As already noted, this study uses the Deaton and Muellbauer (1980) static AIDS specification to model the desired, long-run allocation of consumers' expenditure across non-durable goods (Duffy, 1995, 2001 for critical assessments of various types of advertising-augmented demand systems). An implicit assumption in this approach to model specification is that utility functions are separable with regards to non-durable goods and durable goods. This facilitates the specification and estimation of a complete demand system for non-durable goods. In this paper, therefore, the estimated model should be interpreted as a conditional demand system, which means that any elasticity must be interpreted as measuring the responsiveness of demand for a product with regard to changes in, say, price or advertising for a given level of total non-durables expenditure.[1]

The basic, form of the ith demand equation in the static AIDS is:

$$w_{it} = \alpha_i + \sum_{k=1}^{n} \gamma_{ik} \ln p_{kt} + \beta_i \ln \left(\frac{x_t}{P_t} \right)$$
$$i = 1, 2, \ldots, n; \quad t = 1, 2, \ldots, T \tag{1}$$

where n denotes the number of goods in the system, T is the sample size, w_{it} is the proportion of total, per capita expenditure on all n goods in period t ($x_t = \sum_{k=1}^{n} x_{kt}$) that is allocated to the ith good (i.e. the budget share $w_{it} = x_{it}/\sum_{k=1}^{n} x_{kt}$), p_{kt} is the nominal price of product k in period t, and P_t a general index of prices in the system which is approximated in this study by the Stone (1953) form:

$$\ln P_t = \sum_{k=1}^{n} w_{kt} \ln p_{kt} \tag{2}$$

The α_i, β_i and γ_{ik}, are the (long-run) AIDS parameters, and the intercepts, α_i, can be interpreted as the budget shares for households at subsistence levels of expenditure with prices at base period levels. Advertising is introduced into this specification through 'translation' terms (Pollak and Wales, 1992) which allow the intercepts (the 'baseline' or 'necessary' pattern of consumption) to vary according to a log-linear relationship with real per capita advertising outlays, a_{kt}, on each of the n goods.[2]

Although measurement of total expenditure on a per capita basis is a common feature of applied AIDS studies, calculation of advertising outlays on a per capita basis is perhaps less straightforward and needs some explanation. The advertising variable is measured in real terms (by deflating nominal expenditure by a combined index of television, radio and press media rates) in order to obtain an estimate of the total volume of messages conveyed to the market. This measure is then expressed on a per capita basis in order to obtain an indicator of advertising intensity. Some of the public will notice a message, others will not. As advertising intensity increases, the probability of making a successful 'hit' (message noticed) on a typical consumer will increase and that event may affect consumer behaviour. When expenditures on advertisements are spread more thinly across the population (low per capita advertising), the number of successful hits, and the effectiveness of campaigns, may diminish accordingly. By this reasoning, reductions of the same size in advertising intensity that result either from a cut in total advertising outlays with a constant population, or from population growth in a market where total real advertising expenditure is constant, should have equivalent (negative) effects on per capita consumption. A company that follows a strategy of maintaining constant total real advertising outlays over time will not succeed in maintaining its 'promotional presence' or advertising pressure in a market that is characterised by rapid growth in population (or the number of potential customers). Indeed, it may well lose sales, even though its total real advertising budget is constant, for the simple reason that the proportion of the population that receives the advertising message is likely to decline. For these reasons, advertising is measured in real, per capita terms in this study, which is consistent with much previous practice in the literature (see, for a recent example, Larivière et al. (2000) and the references therein).

There is another 'intercept-shifting' term added to the model: smoking prevalence (S_t), which is the proportion of the population aged 15 and over that

[1] It is worth drawing attention to one implication of this model specification. The conditional price and advertising elasticities that are reported in this paper do not take into account the effects that a product's price or advertising may have upon the prior allocation of total expenditure on all non-durable goods (Edgerton, 1997). In other words, the reported elasticities may under-estimate the full, unconditional effect of price or advertising on individual product demand. This problem could only be avoided by extending the model to include durable goods. That task lies beyond the scope of this paper, but may merit attention in future research.

[2] Translation effects are not the only way of incorporating advertising terms in demand systems (Duffy, 1995). An alternative approach involves advertising scaling effects, whereby advertising may boost the marginal utility of the ith good and reduce its "effective" price. To the extent that this effect operates, it leads to quasi-substitution and income effects that may increase product demand. The comparative results reported in Duffy (1995) are mixed in conclusions and do not favour one approach over another. This paper focuses, therefore, on the translation approach which is easier to estimate and sufficiently general to capture any influence that advertising may have upon demand (see footnote 3).

smokes. Note that the tobacco budget share can be written as:

$$w_{4t} = \frac{x_{4t}}{\sum_{k=1}^{n} x_{kt}} = \frac{x_{4t}^{*}}{\sum_{k=1}^{n} x_{kt}} S_t$$

where x_{4t} and x_{4t}^{*} are, respectively, per capita and per smoker expenditure on tobacco in period t. These equations express the obvious point that the tobacco budget share is influenced by changes in tobacco expenditure per smoker and by changes in smoking prevalence. The huge fall in smoking prevalence that has occurred over the past four decades is likely to have affected demand and budget shares, and it is important to incorporate these shifts in demand into the model specification. For this reason, the logarithm of S_t is included as an additional explanatory variable in all of the demand equations. The other right-hand side variables have to explain, in effect, the other component of changes in the tobacco budget share (per smoker expenditure). There are some other points that are worth making about this variable. First, smoking prevalence is treated as exogenous since attempts to model it were unsuccessful, although this is an issue that may need further attention in future research. Second, S_t must be included in all demand equations in the system because of the consequences of the adding-up conditions (see below): a fall in the tobacco budget share due to reduced smoking prevalence must be offset elsewhere in the system by an equivalent net expansion in one or more other budget shares. The signs on the coefficients attached to the smoking prevalence terms in the various equations may indicate how the pattern of demand has altered across products as consumers have moved away from tobacco, with substitutes for tobacco showing negative prevalence coefficients as they gain new sales from ex-smokers. For goods that many consumers regard as complements to tobacco, which may be the case for some alcoholic drinks, the prevalence coefficient will be positive, indicating that the decline in the incidence of smoking has also reduced their sales.

On the basis of these comments, the intercepts in (1) are deemed to be functions of the logarithmic values of real per capita advertising outlays on the various goods as well as the smoking prevalence rate:

$$\alpha_i = \alpha_{i0} + \sum_{k=1}^{n} \theta_{ik} \ln a_{kt} + \rho_i \ln S_t \quad i = 1, 2, \dots, n$$

where α_{i0}, θ_{ik}, and ρ_i $(i, k = 1, \dots, n)$ are parameters for estimation, and the other terms are as defined above. Substitution of the last equation into (1) allows the augmented, static system to be written as follows:

$$w_i = \alpha_{i0} + \sum_{k=1}^{n} \gamma_{ik} \ln p_k + \sum_{k=1}^{n} \theta_{ik} \ln a_k + \rho_i \ln S + \beta_i \ln(x/P) \quad i = 1, 2, \dots, n \tag{3}$$

Since these equations constitute the long-run demand equations, the time subscript has been omitted and it is important to recognise that the coefficients represent the long-run effects of the explanatory variables on the budget shares. Thus, this specification does not assume that consumer responses to advertising messages are uniform over time, an assumption that has been rejected by several studies (see, for example, Larivière et al. (2000) and references cited therein). Eq. (3) represents, the final, long-run impact of advertising on the pattern of demand. The short-run dynamic profile of responses to changes in advertising, prices etc. is modelled through an error-correction specification (see below). The error-correction specification allows for a flexible pattern of non-uniform consumer responses to advertising over time by allowing for short-run dynamic adjustments of the pattern of demand towards long-run equilibrium.

The adding-up restrictions, which cannot be tested, require:

$$\sum_{i=1}^{n} \alpha_{i0} = 1 \quad \text{and} \quad \sum_{i=1}^{n} \gamma_{ik} = \sum_{i=1}^{n} \theta_{ik} = \sum_{i=1}^{n} \beta_i = \sum_{i=1}^{n} \rho_i = 0 \quad (k = 1, 2, \dots, n) \tag{4}$$

Other, testable restrictions on the parameters are (for $i = 1, 2, \dots, n$):

$$\sum_{k=1}^{n} \gamma_{ik} = 0 \quad \text{[price homogeneity]} \tag{5}$$

and,

$$\gamma_{ik} = \gamma_{ki} \quad (k = 1, 2, \dots, n) \quad \text{[Slutsky symmetry]}. \tag{6}$$

The augmented AIDS in Eq. (3) can be used to test the assertion that advertising has the power to alter the allocation of expenditure by consumers across products. It may be used also to measure the strength of any advertising effects, both in absolute terms and in comparison with the responsiveness of demand to changes in other variables such as prices and 'income' (total real per capita expenditure on all non-durables). These comparisons are best made using (long-run) elasticities which can be calculated as follows:

$$\eta_i = \frac{\beta_i + w_i}{w_i} \quad \text{['income' (expenditure) elasticity]} \tag{7}$$

$$\varepsilon_{ij} = \frac{\gamma_{ij} + w_i w_j}{w_i} - \delta_{ij} \quad \text{[compensated price elasticity]} \tag{8}$$

where $\delta_{ij} = 1$ for $i = j$, and 0 otherwise, and

$$\phi_{ij} = \frac{\theta_{ij}}{w_i} \quad \text{[advertising elasticity].} \tag{9}$$

Throughout, $i, j = 1, 2, \ldots, n$:[3]

2.2. The dynamic model

Eq. (3) can be written more compactly in vector-matrix notation as follows:

$$\boldsymbol{w}_t = \boldsymbol{\Pi} \boldsymbol{x}_t \tag{10}$$

where $\boldsymbol{w}_t$ is a n-vector of budget shares; $\boldsymbol{x}_t$ is a k-vector of intercept, price, advertising, smoking prevalence and real per capita expenditure variables ($k = 2n + 3$); and $\boldsymbol{\Pi}$ is the $(n \times k)$ matrix of long-run AIDS parameters. Eq. (10) represents the long-run, equilibrium position. In the short-run, after changes in any of the elements of $\boldsymbol{x}_t$, the system may be 'out of equilibrium' for some periods as full adjustment to the equilibrium is delayed by inertia that is due to transaction costs, habits and imperfect information. However, the demand system as a whole may be classified as 'cointegrating' if any such disequilibria diminish towards zero for all products over time. This dynamic process of adjustment may be modelled by a vector-autoregressive, distributed lag (VARDL(r, q)) model:

$$\boldsymbol{B}(L)\boldsymbol{w}_t = \boldsymbol{\Gamma}(L)\boldsymbol{x}_t + \boldsymbol{e}_t \tag{11}$$

where $\boldsymbol{B}(L)$ and $\boldsymbol{\Gamma}(L)$ are matrix polynomials of orders r and q, respectively, in the lag operator L, and $\boldsymbol{e}_t$ is an independent, identically distributed random disturbance vector. In practice, estimation is simplified if the orders of the polynomials are identical, $r = q$. Determining the value of q is often accomplished by estimating an initial, relatively high-order VARDL, then testing down for shorter maximum lags in an attempt to obtain a parsimonious, but data-consistent model. In the present case, the heavily parameterised nature of the relatively large, dynamic system (with $n = 7$), coupled with a modest sample size ($T = 133$ before lags are taken), tends to make log-likelihood ratio statistics in the testing sequence somewhat unreliable; as is well-known, the test statistics are prone to over-reject the null hypotheses. Since researchers have often found that relatively low-order vector-autoregressive models will generally suffice in cointegration analysis of seasonally unadjusted data (Johansen, 1995, p. 4), the decision was taken to carry out all estimation and inference within the context of a relatively parsimonious, first-order VARDL ($q = 1$). This does not mean that the dynamic responses of demand to a change in advertising (or any other variable) are constrained to achieve long-run equilibrium in a short period of time. On the contrary, advertising may exert its effects (if any) for many periods after the initial disturbance. Following any immediate, contemporaneous impact of advertising on budget shares, these shares will continue to adjust in subsequent periods due to the influence of the lagged budget shares. These lagged effects persist into the next period, and subsequent periods stretching into the distant future. An attractive feature of the first-order VARDL AIDS is that it allows long lags not only of advertising for all the different goods in the system but also of their prices and previous

[3] It has been suggested that advertising may rotate demand curves. Demand becomes more elastic if advertising is an instrument for increasing competition and flows of information about the availability of substitutes. On the other hand, advertising can make demand more inelastic by reducing competition through the establishment of barriers to entry, and by creating brand and product loyalty. The model specification used in this paper is sufficiently flexible to accommodate these different effects. The own-product price elasticity in Eq. (8) varies with the ith budget share. This budget share, in turn, may be influenced by advertising in Eq. (3). Hence, advertising can rotate the demand curve in this model. From Eq. (8) $\partial\varepsilon_{ij}/\partial w_i = (w_i^2 - \gamma_{ii})/w_i^2$. This term may be greater than, equal to, or less than zero, and varies with the ith budget share as it changes over time.

budget shares (as well as total expenditure) to affect the observed pattern of demand.[4] This is a very flexible and comprehensive approach to dynamic specification.

As a first-order system, (11) is written thus:

$$[\boldsymbol{I} + \boldsymbol{B}_1(L)]\boldsymbol{w}_t = [\boldsymbol{\Gamma}_0 + \boldsymbol{\Gamma}_1(L)]\boldsymbol{x}_t + \boldsymbol{e}_t \qquad (12)$$

The matrix of parameters $\boldsymbol{\Pi}$ in the long-run AIDS can be obtained from estimates of the VARDL model in (12) by considering the equation's steady-state solution:

$$\bar{\boldsymbol{w}} = \boldsymbol{\Pi}\bar{\boldsymbol{x}}$$

where

$$\boldsymbol{\Pi} = [\boldsymbol{I} + \boldsymbol{B}_1]^{-1}[\boldsymbol{\Gamma}_0 + \boldsymbol{\Gamma}_1] \qquad (13)$$

However, the matrix operations in (13) are cumbersome, and a more convenient, direct way of recovering the matrix of long-run parameters from the dynamic model (12) is to estimate a reparameterised, error-correction version of the VARDL system.

A re-arranged version of (12) can be written thus:

$$\boldsymbol{w}_t = \boldsymbol{\Gamma}_0\boldsymbol{x}_t + \boldsymbol{\Gamma}_1\boldsymbol{x}_{t-1} - \boldsymbol{B}_1\boldsymbol{w}_{t-1} + \boldsymbol{e}_t$$

so

$$\Delta\boldsymbol{w}_t = \boldsymbol{\Gamma}_0\boldsymbol{x}_t + \boldsymbol{\Gamma}_1\boldsymbol{x}_{t-1} - (\boldsymbol{I} + \boldsymbol{B}_1)\boldsymbol{w}_{t-1} + \boldsymbol{e}_t$$

and

$$\Delta\boldsymbol{w}_t = \boldsymbol{\Gamma}_0\Delta\boldsymbol{x}_t + (\boldsymbol{\Gamma}_0 + \boldsymbol{\Gamma}_1)\boldsymbol{x}_{t-1} - (\boldsymbol{I} + \boldsymbol{B}_1)\boldsymbol{w}_{t-1} + \boldsymbol{e}_t$$

This last equation can be written as an 'error-correction' model:

$$\Delta\boldsymbol{w}_t = \boldsymbol{A}_0\Delta\boldsymbol{x}_t + \boldsymbol{D}[\boldsymbol{w}_{t-1} - \boldsymbol{\Pi}\boldsymbol{x}_{t-1}] + \boldsymbol{e}_t \qquad (14)$$

where

$$\boldsymbol{A}_0 = \boldsymbol{\Gamma}_0$$

$$\boldsymbol{D} = -(\boldsymbol{I} + \boldsymbol{B}_1)$$

$$\boldsymbol{\Pi} = [\boldsymbol{I} + \boldsymbol{B}_1]^{-1}[\boldsymbol{\Gamma}_0 + \boldsymbol{\Gamma}_1]$$

Although Eqs. (12) and (14) are observationally equivalent, estimation of the error-correction form has the crucial advantage of yielding a direct estimate of the matrix of long-run parameters, $\boldsymbol{\Pi}$. Various restrictions on these parameters can subsequently be tested.

As it stands, Eq. (14) cannot be estimated since the right-hand side variables in each equation are perfectly collinear as a consequence of the budget shares summing to unity and the equations containing constant terms. Anderson and Blundell (1982, 1983) derive a number of restrictions that must be imposed on (14) for estimation to be feasible. As a consequence of the adding-up conditions, the last element of $\boldsymbol{w}_t$and the bottom row of $\boldsymbol{\Pi}$ must be deleted (the omitted row of $\boldsymbol{\Pi}$ can be recovered subsequently from the adding-up condition that the columns of $\boldsymbol{\Pi}$ must sum to zero). In addition, the constant term and the three seasonal dummies must be omitted from x_t when the elements are differenced.

The error-correction model in (14) implies certain types of consumer behaviour over time. It implies that once consumers have reached their long-run, optimising allocation of expenditure across products, they will have in each period thenceforth a 'baseline' plan: to allocate their budgeted expenditure across products in the current period in precisely the same way as in the last period, so that $\Delta\boldsymbol{w}_t = 0$. In other words, once a pattern of expenditure has been chosen on the basis of previous experience and information about prices, advertising and incomes, consumers do not revise that pattern 'without good reason'.

This baseline pattern will be modified as consumers become aware of new information that has become available since the previous period for example on prices, income, advertising or even health risks. This impact of new information is captured by the first term on the right-hand side of (14), $\boldsymbol{A}_0\Delta\boldsymbol{x}_t$. In addition, budget shares may be changed in the current period even in the absence of new information since the last period. This is due to the term in square brackets on the right-hand side of (14): $\boldsymbol{D}[\boldsymbol{w}_{t-1} - \boldsymbol{\Pi}\boldsymbol{x}_{t-1}]$. This is the error-correction term, being the deviation of actual budget shares in the previous period, $\boldsymbol{w}_{t-1}$, from the values that were desired on the basis of the information available then, $\boldsymbol{w}^*_{t-1} = \boldsymbol{\Pi}\boldsymbol{x}_{t-1}$ (where

[4] Lagged effects are likely to be important in the demand for alcohol and tobacco (and even the other goods, but perhaps to a lesser extent) because of the influence of habit formation. The latter effect is often modelled by inclusion of a first-order lagged value of the consumption variable, and the present model generalises this approach by including the lagged budget shares of all the goods in the system in each equation. In other words, this model incorporates a broader, interdependent, multi-good measure of the influence of habits.

the asterisk denotes a desired value). Consumers in the current period attempt to change $\boldsymbol{w}_t$ from its value in the previous period, $\boldsymbol{w}_{t-1}$, with the aim of closing some of the gap that may have existed between $\boldsymbol{w}_{t-1}$ and $\boldsymbol{w}^*_{t-1}$. These adjustments move budget shares in the direction of their desired values, eventually establishing long-run equilibrium with $\boldsymbol{w}_t = \boldsymbol{\Pi x}_t$.

The speed of adjustment of the ith budget share towards its desired value is governed not only by the ith element on the leading diagonal of the loading matrix $\boldsymbol{D}$: these coefficients, the d_{ii}, may be termed the 'own-adjustment coefficients' and are expected to be negative. The speed of adjustment of the ith budget share is also affected by the non-zero, off-diagonal elements of this matrix, the d_{ij} $(i \neq j)$, for these 'cross-adjustment coefficients' measure the extent to which adjustments in a particular budget share depend on the deviations from equilibrium of other budget shares in the system. Adjustments in the various markets may be highly inter-related, with pronounced 'spill-over' effects.

3. Data sources and time series properties

All the data series used in this study span the period 1963, first quarter, to 1996, first quarter. All primary series are quarterly and seasonally unadjusted, unless noted otherwise. Quarterly data represent the highest frequency obtainable for these series and this frequency seems to be preferable to annual data for an advertising study since consumer responses to advertising campaigns may exert their greatest influence over a matter of weeks and months rather than years (Clarke, 1976). Seasonally adjusted data are avoided since prior smoothing of the data may lead to distorted estimates of the dynamics of the system (Wallis, 1974).

The budget shares w_{it} are calculated as the ratio of consumers' expenditure at current prices on the ith product to total consumers' expenditure at current prices on all non-durable goods and services in the UK. Prices p_i are calculated as implicit deflators, that is the ratio for each product of consumers' expenditure at current prices to consumers' expenditure at constant (1990) prices. All of the consumer expenditure series, real and nominal, are taken from the Office for National Statistics (ONS) Data Bank at the University of Manchester Computing Centre. The total real per capita expenditure term $\ln(x_t/P_t)$ is calculated as the logarithm of the ratio of total consumers' expenditure on non-durables to total UK population less the logarithmic value of the Stone price index as defined in (2). The UK population series is only published at annual frequency (*Monthly Digest of Statistics*, ONS, various issues), so it was interpolated to quarterly frequency by means of the method described in Boot et al. (1967) that minimises the squared second differences of the interpolated figures, subject to the constraint that the latter average to the annual figure.

Quarterly observations for nominal advertising expenditure are obtained from various issues of *Statistical Review of Press and TV Advertising* (Legion Publishing Services) and the *MEAL Quarterly Digest of Advertising Expenditure* (Media Expenditure Analysis Ltd.). These series are transformed to a real, per capita basis by deflating the advertising data by the product of the UK population and an index of press and television rates. The media rates index is abstracted on an annual basis from *The Advertising Statistics Yearbook* (Advertising Association, various years), and interpolated to quarterly frequency using the Boot et al. (1967) procedure.

Separate series for total expenditure on television, radio and press advertising on beer, spirits, wine, tobacco and food and soft drink are taken from the MEAL categories with those names. Advertising on clothing and footwear is represented by the MEAL category 'Wearing Apparel'. Advertising on other non-durables is measured in this study as the sum of advertising outlays in the MEAL categories 'Household Stores and Services', 'Pharmaceuticals' and 'Toiletries and Cosmetics'.

Annual observations for smoking prevalence, S_t, measured as the proportion of the population aged 15 years or over who smoke cigarettes (manufactured or hand-rolled), are interpolated to quarterly frequency using the Boot et al. (1967) procedure. *Statistics of Smoking in the UK* (Tobacco Research Council) and *Social Trends* (CSO), various issues, provide the primary annual data.

It is common practice to test for stationarity and orders of integration in time series data before attempting to estimate long-run, cointegrating relationships. It is important to establish these univariate properties when attempting to estimate a long-term, or cointegrating, demand relationship because the left- and right-hand sides of that relationship need to be 'balanced', in the sense that they must be integrated to the same order (Granger, 1981). Many economic series are integrated of order one, denoted $I(1)$. That is, they are non-stationary in levels, but their first differences are stationary.

For studies that employ quarterly, seasonally unadjusted data, the concept of integration is often broadened to allow for a mixture of first and fourth differencing being required to attain stationarity. Osborn et al. (1988) use the notation $I(a, b)$ to summarise the required mixture, with the first argument indicating the order of non-seasonal (first) differencing and the second argument the order of seasonal differencing necessary for stationarity. Thus, a quarterly series is said to be $I(1, 1)$ if it requires both one quarter and seasonal (four quarter) differencing to become stationary. An $I(0, 1)$ series requires only seasonal differencing, an $I(1, 0)$ series needs only one quarter differencing, and an $I(0, 0)$ series is stationary in levels and does not need differencing.

The unit root testing procedure of Hylleberg et al. (1990) is used to investigate the time series properties of the above data. Test results are presented in Table 1. These tests have an $I(0, 1)$ process as the null hypothesis for a series X_t and they are based on the following regression after augmentation with lagged dependent variables and deterministic components:

$$Y_{4t} = \pi_1 Y_{t-1} + \pi_2 Y2t - 1 + \pi_3 Y_{3t-2} + \pi_4 Y_{3t-1} \tag{15}$$

Table 1
Seasonal unit root test results (Hylleberg et al., 1990)

Variable	t-statistic for π_1	F_{234}	F_{1234}	Augmentation lags	Conclusion
Budget shares					
w_1 (beer)	−2.64	13.08*	11.52*	–	$I(1, 0)$
w_2 (spirits)	−0.66	3.34	2.60	1, 4	$I(0, 1)$
w_3 (wine)	−2.09	7.47*	8.68*	1	$I(1, 0)$
w_4 (tobacco)	−1.48	7.50*	6.47*	1	$I(1, 0)$
w_5 (food and soft drink)	−1.60	4.88	4.33	1	$I(0, 1)$
w_6 (clothing and footwear)	−2.99	6.98*	8.17*	1, 2	$I(1, 0)$
w_7 (other non-durables)	−1.65	7.95*	7.03*	1	$I(1, 0)$
Expenditure (real, per capita, non-durable goods and services)					
$\ln(x_t/P_t)$	−3.16	2.54	4.59	1, 4, 5	$I(0, 1)$
Prices					
p_1 (beer)	−1.68	20.76*	17.65*	1	$I(1, 0)$
p_2 (spirits)	−2.41	3.00	4.32	1, 4, 5	$I(0, 1)$
p_3 (wine)	−0.72	278.93*	211.30*	–	$I(1, 0)$
p_4 (tobacco)	−2.39	19.06*	17.54*	1	$I(1, 0)$
p_5 (food and soft drink)	−2.42	8.28*	8.74*	1, 2, 3, 4, 5	$I(1, 0)$
p_6 (clothing and footwear)	−1.90	8.65*	7.49*	1, 4, 8	$I(1, 0)$
p_7 (other non-durables)	−1.28	2.82	2.62	1, 4, 5, 8, 9	$I(0, 1)$
Advertising (real, per capita)					
a_1 (beer)	−2.59	8.77*	8.55*	1, 3, 5	$I(1, 0)$
a_2 (spirits)	−3.19	11.63*	11.70*	2, 4, 5	$I(1, 0)$
a_3 (wine)	−2.11	4.80	4.88	3	$I(0, 1)$
a_4 (tobacco)	−2.93	28.48*	22.49*	–	$I(1, 0)$
a_5 (food and soft drink)	−2.48	12.20*	10.92*	1, 6	$I(1, 0)$
a_6 (clothing and footwear)	−0.60	9.32*	6.99*	4	$I(1, 0)$
a_7 (other non-durables)	−1.88	23.16*	18.50*	–	$I(1, 0)$
Critical values (5%)	−3.53	5.99	6.47		

Notes: The symbol (∗) in the superscript indicates rejection at the 5% level of the null hypothesis of zero coefficient (or coefficients) in Eq. (15). The 5% critical values are taken from Ghysels et al. (1994); they are appropriate for a test regression that includes a constant, seasonal dummies, a linear trend and which is estimated from a sample size of 100 observations. All the variables, apart from budget shares, are transformed to logarithmic values prior to testing.

where

$$Y_{1t} = (1 + L + L^2 + L^3)X_t$$

$$Y_{2t} = -(1 - L + L^2 - L^3)X_t$$

$$Y_{3t} = -(1 - L^2)X_t$$

$$Y_{4t} = (1 - L^4)X_t$$

Eq. (15) is estimated initially with all lagged values of the dependent variable up to a maximum lag of eight quarters, plus a constant, trend and three seasonal dummies.[5] A testing down procedure is then followed to eliminate insignificant lagged values of the dependent variable, working from the longest lags towards the shortest, but always subject to the condition that the residuals exhibited no evidence of serial correlation up to the fourth order.

Failure to reject the null hypothesis that X_t is $I(0, 1)$ requires that all $\pi_i = 0$ ($i = 1, 2, 3, 4$). This is tested by a joint F statistic, denoted as F_{1234} in Table 1. The alternative hypotheses that are worth considering are that each variable is $I(1, 0)$ or $I(0, 0)$. These hypotheses require the use of the t-statistic for π_1 and a joint F-type test on $\pi_2 = \pi_3 = \pi_4 = 0$ (denoted as F_{234} in the table); an insignificant t-value for π_1 combined with a significant F_{234} statistic implies that the series is $I(1, 0)$, whilst a significant t-statistic for π_1 and a significant F_{234} statistic indicates that the series is $I(0, 0)$.

The F_{1234} statistics in Table 1 indicate that the majority of the series used in this study (16 out of 22) are not $I(0, 1)$. The conjunction of insignificant t-ratios for π_1 (implying non-rejection of $\pi_1 = 0$) and significant values for F_{234} (rejecting the presence of unit roots at the seasonal frequency) leads to the conclusion that the majority of the series are $I(1, 0)$. Budget shares are, of course, bounded between 0 and 1, so they must be stationary over the long-run. Tests which suggest that the shares are non-stationary are, therefore, somewhat problematic. Nevertheless, the test conclusions for this group indicate that, over the sample period at least, most (five out of seven) of the budget shares are $I(1, 0)$.

Whilst some of the variables, including expenditure appear to be $I(0, 1)$, most (almost 3/4) of the series are $I(1, 0)$. It is hoped that this similarity in properties across the great majority of the series will facilitate the estimation of a meaningful (non-spurious) set of cointegrating, long-term demand relationships. For the remainder of this paper, it is assumed that seasonality in the series can be modelled as deterministic (rather than stochastic) processes by the inclusion of seasonal dummy variables in the demand equations.

The next issue to be addressed concerns the exogeneity or endogeneity of the explanatory variables. It may be the case that prices can be treated as exogenous if it is assumed, along 'Keynesian' lines, that goods prices in these markets are 'sticky' and characterised by inertia in the presence of shocks. Well-known sources of price rigidities include 'menu costs', price contracts, oligopolistic and imperfectly competitive industrial structures and the dominant effects on price changes (in the cases of alcoholic drinks and tobacco) of taxation. In demand system studies, it is also frequently assumed that the total expenditure term is exogenous, but it is not clear that the same assumption can be made about advertising outlays. If advertising budgets, for example, are related to current sales, but also affect sales, then there may be simultaneous interaction between consumer demand and advertising. In that case, the advertising variables should be treated as members of the set of jointly endogenous variables, which would have important implications for model specification and estimation. The exogeneity of these variables is ultimately an empirical question. Therefore, Hausman–Wu (Wu, 1983) tests of the null hypotheses that prices, advertising and total expenditure are independent of the equation disturbances are carried out. The test results are displayed in Table 2. Test statistics are distributed asymptotically as central $\chi^2(n)$ under the null hypothesis that the n variables which feature in a test are orthogonal to an equation's disturbances. The null hypothesis is not rejected at the 5% level in the great majority of the tests. The tests indicate that total non-durable goods expenditure may be correlated with the alcoholic drink and tobacco disturbances. For all other variables, in all of the equations, the tests fail to reject the null hypothesis of exogeneity. On the basis of these results, it seems reasonably safe to proceed on the assumption that prices, advertising and expenditure are indeed exogenous.

[5] The price of other non-durables, for which the maximum lag on the augmentation terms was extended above eight quarters in order to eliminate serial correlation in the residuals, represents an exception.

Table 2
Hausman–Wu tests of advertising exogeneity

Consumption category	Test statistics		
	Prices[a]	Advertising[a]	Expenditure[b]
(1) Beer	0.82	4.81	7.04
(2) Spirits	2.44	0.35	43.32
(3) Wine	0.39	2.74	9.49
(4) Tobacco	0.91	2.61	12.83
(5) Food and soft drink	1.13	3.41	0.02
(6) Clothing and footwear	2.03	4.22	2.13
(7) Other non-durables	1.33	0.29	2.34

The tests employed the following set of instruments: a constant and three centred seasonal dummies; budget shares for categories 1–6, lagged one quarter; current and one quarter lagged logarithmic values of prices and real per capita advertising, all seven categories; current and one quarter lagged logarithmic values of real per capita expenditure on non-durable consumer goods and the smoking participation rate; the current period logarithmic values of total population, index of media rates, the UK Treasury Bill rate, the gross flat yield on UK Government Consols and total nominal expenditure on non-durables; the annual rate of growth of nominal GDP, and the velocity of circulation of the broad money stock (M4). The choice of instruments was influenced by Schmalensee's (1972) analysis of the determinants of optimal advertising by oligopolistic firms, but with extra variables (such as the rate of growth of 'money' GDP) added to capture possible business cycle/expectations effects upon consumers expenditure and advertising budgets.

[a] The critical value of $\chi^2(7)$ at the 5% level is 14.07.

[b] The critical value of $\chi^2(1)$ at the 5% level is 3.84.

4. Empirical results

The equations in (14) are estimated in the TSP package using the multivariate least-squares option which assumes that there are no simultaneity problems with endogenous variables on the right-hand sides of the equations, but which allows for contemporaneous correlation between the equations' disturbances. The model is estimated without any prior restrictions being imposed, and then price-homogeneity and price-symmetry constraints are imposed and tested in re-estimation runs. These restrictions can help to reduce the dimensionality of the problem and increase the degrees of freedom in estimation. Hence, where the restrictions are consistent with the data, they should serve to increase the efficiency of the estimates. In two final estimation runs, all prices and then all advertising variables are removed from the long-run demand functions in order to test for their contribution to the model's fit. These two versions of the model are referred to as the 'restricted price responses' and the 'restricted advertising responses' models, respectively.

A testing down process is carried out through a sequence of likelihood ratio (LR) tests, starting with the most general, unrestricted specification, then considering increasingly restrictive hypotheses in the following order: the relatively weak restriction of price homogeneity, the strong symmetry restrictions, and finally the restricted price responses and restricted advertising responses models. In order to restrain the significance level to approximately 5% for the overall implicit test of the most restricted hypothesis against the initial maintained hypothesis, each individual set of restrictions is tested at the 1% level. Test statistics for the error-correction model are set out in the upper part of Table 3. For comparison, the lower part of the table contains test statistics which have been derived from estimates of the static AIDS of Eq. (3).

It was noted above that the LR test has a well-known tendency to over-reject the null hypothesis in heavily parameterised models which have been estimated with relatively small samples. In an attempt to correct for this bias, several arbitrary, small sample adjustments to the test statistics have been suggested in the literature. Use is made here of the degrees of freedom adjustments to the LR statistics suggested by Pudney (1981): these are denoted by LR* in Table 3. As a further check, the table also contains statistics, denoted by LR**, which have been adjusted by a small sample factor suggested by Anderson (1958).

When the unadjusted LR statistics are used in the test procedure for the error-correction model, the model which imposes price homogeneity and

Table 3
Likelihood ratio tests for price homogeneity and symmetry

H_1	H_0	n_p^1	n_p^0	χ^2_{CRIT}	LR	LR*	LR**
(a) Dynamic (error correction) AIDS (14)							
Unrestricted	Homogeneity	252	246	16.81	16.40	7.65	10.81
Homogeneity	Homogeneity plus symmetry	246	231	30.58	28.42	6.96	19.11
Homogeneity plus symmetry	Restricted price responses	231	210	38.93	172.54	143.43	119.93
Homogeneity plus symmetry	Homogeneity, symmetry and restricted advertising responses	231	189	66.18	86.44	29.26	61.23
(b) Static AIDS (3)							
Unrestricted	Homogeneity	120	114	16.81	37.26	30.22	30.77
Homogeneity	Homogeneity plus symmetry	114	99	30.58	53.66	36.33	45.02
Homogeneity plus symmetry	Restricted price responses	99	78	38.93	377.64	353.64	325.12
Homogeneity plus symmetry	Homogeneity, symmetry, and restricted advertising responses	99	57	66.18	132.76	86.16	116.16

Note: H_0 and H_1 denote the null and alternative hypotheses, respectively and n_p^0 and n_p^1 indicate the number of freely estimated parameters under the null and alternative hypotheses, respectively. The χ^2_{CRIT} is the χ^2 critical value, 1% significance level, with degrees of freedom equal to $n_p^1 - n_p^0$. LR is the unadjusted likelihood ratio statistic. LR* is the 'Pudney-adjusted', and LR** is the 'Anderson-adjusted' LR statistic.

symmetry constraints is unambiguously the most restricted model that is consistent with the data. This is a robust conclusion in the sense that it is arrived at without recourse to small sample adjustments. Use of the adjusted statistics (LR* and LR**) simply reinforces the conclusion that price homogeneity and symmetry restrictions are acceptable.

The restricted price responses model, which sets all long-run price coefficients to zero, is rejected by the unadjusted and the small sample adjusted LR tests. The inter-product allocation of demand is definitely affected by relative prices and this too is a robust conclusion. However, the restricted advertising response model (which sets all long-run advertising effects to zero) is rejected by the unadjusted LR statistic but accepted by the adjusted versions of the test. The test results in this case are ambiguous and it is not altogether clear whether advertising does or does not affect the overall distribution of consumer demand. Although it was decided to give the variable the 'benefit of the doubt' and retain advertising in the analysis for the remainder of this paper, these ambiguous test results raise a suspicion that advertising's effects on the pattern of demand may be of marginal significance and probably much weaker than those of prices.

It is interesting to carry out, for comparison, the same sequence of tests on estimates of static versions of the model, notwithstanding the rejection of this model in a LR test comparison with the error-correction parametrisation of the first-order VARDL model within which it is nested.[6] The results are displayed in the lower part of Table 3, where it may be seen that homogeneity and symmetry are rejected by both the unadjusted and the adjusted LR statistics, in stark contrast to the conclusion reached in the testing sequence for the error-correction model above. This conclusion for the static model may support the previously stated hypothesis that the restrictions of economic theory are more likely to be satisfied in the long-run, when full adjustment to shocks has occurred, than in the short-run. If that hypothesis is valid, then the restrictions of demand theory should be discernible in the estimates of the error-correction model, which separates long-run from short-run behaviour. The static model is based on a different hypothesis, which is that short-run and long-run behaviour do not differ: the consumer is always in 'equilibrium'. If the two aspects of behaviour differ, however, then their conflation within the static model will induce mis-specification bias in the estimates, which may account for the rejection of the homogeneity and symmetry restrictions in that case. Doubts about the reliability of the static model estimates also

[6] With the static model as the null and the first-order VARDL as the alternative hypothesis and degrees of freedom is equal to 132, the test statistics are: LR = 479.48; LR* = 304.99; and LR** = 351.25.

diminish confidence in the test results in the last row of Table 3 which suggest that non-zero advertising effects are present in the long-run model of demand.[7]

Tables 4 and 5 contains the estimated values of the long-run parameters in $\boldsymbol{\Pi}$ from the homogeneity- and symmetry-constrained version of the error-correction model in Eq. (14), and Tables 6 and 7 presents the estimated values of the short-run responses in $\boldsymbol{A}_0$. Table 8 reports the estimates of the various elasticities, whilst Table 9 presents the estimated loading matrix $\boldsymbol{D}$.

The main features of the empirical results in these tables may be summarised as follows:

(i) Several of the price, advertising and expenditure coefficients in Tables 4 and 5 are significantly different from zero, although it is easier to discuss these effects in terms of elasticities (see below). To note one surprise, attention is drawn to the insignificance of the coefficient on the smoking prevalence variable in the tobacco equation, although it does have the 'correct', positive sign. The significant estimates of the coefficients on this variable in other demand equations suggest that food and soft drink consumption may have benefited, but spirits consumption may have suffered, from increased rates of abstention from smoking. The coefficients on $\ln S_t$ in the other equations are insignificantly different from zero.

(ii) Only 25% of the 96 short-term adjustment coefficients in the matrix A_0 (Tables 6 and 7) are significantly different from zero. Changes in prices, advertising, total expenditure and smoking participation have some direct influence on short-run adjustment of budget shares, but most of the effects of these changes are delayed and come through gradually over several periods via the error-correction terms in each equation. The error-correction terms most likely reflect the inertia in demand patterns that arises from the force of habit in consumer behaviour.

(iii) All of the own-price elasticities in Table 8 are negative, as predicted by demand theory, and most are significantly different from zero. These estimates, together with the numerous, significant cross-price elasticity estimates, confirm the important role that prices play in the determination of the inter-product distribution of demand.

(iv) The estimated long-run own-price elasticities are in general quite plausible and similar to estimates that have been reported in other studies.[8] Thus, the small beer price elasticity of −0.4 is close to the −0.55 to −0.7 range reported in Duffy (1991a). The relatively high spirits price elasticity of −1.4 is close to many estimates from other studies, but the wine price elasticity is in the inelastic range and well outside the −1.7 to −2.2 range which has been presented in other studies (Duffy (1991a). All of the estimated cross-elasticities of demand between the 'vices' (beer, spirits, wine and tobacco) are insignificant, although it is wise to keep an open mind on this matter since other studies (Walsh, 1982; Duffy, 2001) have discerned a significant amount of substitutability between these goods. The low tobacco price elasticity estimate of −0.4 corresponds to other estimates, including the Treasury figure used in tax simulations (Duffy, 1991a). The price elasticity of demand for food is very low at −0.1, but not far from values reported in other studies: Tiffin and Tiffin (1999) calculate that the Hicksian own-price elasticity of all food for UK is −0.038. It is quite plausible that the demand for a group of necessities, clothing and footwear, will be price inelastic, and the reported elasticity (−0.38) is very similar to an estimate (−0.33) presented in the earlier study by Duffy (1991b). In short, most of the estimates of the own-price elasticities that are set out in this paper seem to be quite reliable, although the responsiveness of wine demand to price (and total expenditure, see below) may need revisiting in future research.

(v) Advertising's impact, if it has one, on the inter-product distribution of demand is very

[7] In any case, the rejection of the 'restricted advertising responses' model is conditional on homogeneity and symmetry, both of which are rejected earlier in the testing sequence (see the first two rows of part (b) of Table 3).

[8] It must be borne in mind that, as already noted, these are conditional elasticities and must be interpreted as such. AIDS models always condition demand upon a given total expenditure on all goods in the system. All elasticities derived from AIDS models (in the absence of further adjustment) are conditional elasticities (Duffy, 1991b; Tiffin and Tiffin, 1999). The cross-study comparisons made here relate mainly to demand systems that are conditioned on total non-durable goods expenditure.

Table 4
Estimates of the long-run preference parameters from the error-correction model for prices

Product	Prices						
	ln $p1$	ln $p2$	ln $p3$	ln $p4$	ln $p5$	ln $p6$	ln $p7$
(1) Beer	0.0378 (2.7797)	0.0064 (0.9237)	−0.0050 (0.7075)	−0.0050 (0.7075)	−0.0143 (1.1740)	−0.0032 (0.3163)	−0.0172 (1.5240)
(2) Spirits	–	−0.0129 (2.3778)	−0.0075 (1.4426)	−0.0073 (1.8867)	0.0172 (2.2197)	−0.0087 (1.3267)	0.0127 (1.8275)
(3) Wine	–	–	0.0045 (0.5524)	0.0036 (0.6607)	0.0278 (2.7696)	−0.0418 (4.7343)	0.0184 (1.9883)
(4) Tobacco	–	–	–	0.0387 (5.4527)	−0.0214 (2.1570)	0.0278 (3.0620)	−0.0369 (3.7251)
(5) Food and soft drink	–	–	–	–	0.1777 (7.6468)	−0.0150 (0.8396)	−0.1722 (9.7631)
(6) Clothing and footwear						0.0659 (3.3088)	−0.0249 (1.3329)
(7) Other non-durables	–	–	–		–	–	0.2201 (8.2637)

Homogeneity and symmetry imposed. The coefficients for product group 7 were derived from the adding-up constraints. The t-ratios are given in parentheses.

Table 5
Estimates of the long-run preference parameters from the error-correction model for advertising, expenditure and smoking participation

Product	Advertising							Expenditure	Smoking participation
	$\ln a_1$	$\ln a_2$	$\ln a_3$	$\ln a_4$	$\ln a_5$	$\ln a_6$	$\ln a_7$	$\ln x_t/P_t$	$\ln S_t$
(1) Beer	0.0047 (2.2935)	−0.0036 (2.6367)	−0.0001 (0.0609)	0.0035 (2.0100)	0.0007 (0.2597)	−0.0035 (1.5984)	−0.0097 (2.7116)	−0.0016 (0.1078)	0.0151 (1.1791)
(2) Spirits	−0.0005 (0.3889)	0.0001 (0.0573)	0.0013 (1.1811)	−0.00001 (0.0104)	−0.0055 (2.8537)	−0.0012 (0.7686)	0.0075 (3.0665)	0.0196 (2.1307)	0.0315 (3.6231)
(3) Wine	−0.0009 (0.4024)	−0.0001 (0.0459)	0.0002 (0.1159)	−0.0034 (1.8230)	−0.0005 (0.1587)	−0.0060 (2.5339)	0.0133 (3.5422)	−0.0070 (0.5179)	0.0179 (1.3225)
(4) Tobacco	0.0020 (0.7715)	−0.1019 (0.5755)	−0.0011 (0.4942)	0.0043 (1.8459)	−0.0029 (0.7703)	0.00793 (2.7081)	−0.0015 (0.3595)	−0.0446 (2.7411)	0.0189 (1.2189)
(5) Food and soft drink	−0.0046 (1.1165)	−0.0025 (0.9034)	0.0067 (1.9772)	0.0007 (0.2064)	−0.0006 (0.1042)	0.0076 (1.6720)	−0.0191 (2.7093)	−0.2297 (8.8092)	−0.0838 (3.4229)
(6) Clothing and footwear	−0.0061 (1.0562)	0.0042 (1.0709)	0.0022 (0.4415)	−0.0085 (1.6479)	−0.0003 (0.0393)	−0.0119 (1.8159)	0.0141 (1.5268)	−0.0172 (0.4788)	0.0065 (0.2064)
(7) Other non-durables	0.0054 (0.7905)	0.0029 (0.6225)	−0.0093 (1.6011)	0.0033 (0.5508)	0.0090 (0.9235)	0.0070 (0.9085)	−0.0047 (0.4306)	0.2805 (6.5911)	−0.0061 (0.1738)

Homogeneity and symmetry imposed. The coefficients for product group 7 were derived from the adding-up constraints. The t-ratios are given in parentheses.

Table 6
Estimates of the short-run responses in A_0 for prices

Product	Prices						
	$\Delta \ln p_1$	$\Delta \ln p_2$	$\Delta \ln p_3$	$\Delta \ln p_4$	$\ln p_5$	$\Delta \ln p_6$	$\Delta \ln p_7$
(1) Beer	0.0735 (3.9258)	−0.0015 (0.1243)	−0.0524 (3.0179)	−0.0139 (1.2253)	0.0227 (1.1874)	0.0180 (0.7615)	0.0084 (0.5198)
(2) Spirits	0.0110 (0.9549)	−0.0013 (0.1581)	−0.0065 (0.5901)	0.0002 (0.0243)	−0.0226 (1.8977)	−0.0138 (0.9325)	−0.0240 (2.3672)
(3) Wine	0.0003 (0.0331)	−0.0055 (0.8033)	0.0027 (0.2759)	0.0041 (0.6533)	0.0192 (1.8259)	−0.0397 (2.9990)	0.0240 (2.6633)
(4) Tobacco	−0.0070 (0.6048)	−0.0171 (2.1971)	−0.0019 (0.1665)	0.0428 (5.7743)	−0.0564 (4.6299)	−0.0235 (1.5326)	0.0193 (1.8336)
(5) Food and soft drink	−0.0990 (4.0235)	0.0333 (2.0375)	−0.0120 (0.5130)	−0.0042 (0.2770)	0.1508 (5.7296)	−0.0136 (0.4236)	−0.0184 (0.8378)
(6) Clothing and footwear	0.0122 (0.5958)	−0.0117 (0.8561)	0.0422 (2.1246)	−0.0348 (2.7159)	−0.0054 (0.2572)	0.0581 (2.1329)	−0.0941 (5.0480)

Seasonal dummy variables' coefficients omitted.

Table 7
Estimates of the short-run responses in A_0 for advertising, expenditure and smoking participation

Product	Advertising							Expenditure	Smoking participation
	$\Delta \ln a_1$	$\Delta \ln a_2$	$\Delta \ln a_3$	$\Delta \ln a_4$	$\Delta \ln a_5$	$\Delta \ln a_6$	$\Delta \ln a_7$	$\Delta \ln x_t/P_t$	$\ln S_t$
(1) Beer	0.0017 (1.1960)	−0.0004 (0.3628)	0.0002 (0.2471)	0.0001 (0.0444)	0.0008 (0.3809)	−0.0033 (2.3232)	0.0009 (0.2886)	−0.0256 (1.5506)	−0.0464 (1.0805)
(2) Spirits	−0.0001 (0.1377)	0.0010 (1.5969)	0.0007 (1.3354)	0.0004 (0.5206)	−0.0037 (2.7793)	−0.0004 (0.4094)	0.0025 (1.2661)	−0.0140 (1.3620)	0.0226 (0.8406)
(3) Wine	−0.0014 (1.8399)	0.0006 (1.0511)	0.0006 (1.2186)	−0.0003 (0.4208)	0.0008 (0.6523)	−0.0022 (2.7908)	0.0028 (1.5598)	0.0119 (1.3086)	0.0034 (0.1421)
(4) Tobacco	0.0023 (2.4967)	0.0006 (0.9755)	−0.0033 (5.7552)	0.0014 (1.5759)	0.00004 (0.0305)	0.0019 (2.0189)	0.0027 (1.3372)	−0.0401 (3.7938)	0.0379 (1.3611)
(5) Food and soft drink	−0.0038 (1.9903)	−0.0008 (0.5948)	0.0045 (3.7198)	−0.0009 (0.5069)	0.0036 (1.2606)	0.0025 (1.2995)	−0.0056 (1.2945)	−0.1212 (5.4743)	−0.2127 (3.6791)
(6) Clothing and footwear	−0.0007 (0.4672)	−0.0005 (0.4228)	0.0015 (1.5138)	−0.0003 (0.1713)	0.0004 (0.1746)	0.0020 (1.2373)	−0.0055 (1.5293)	−0.0003 (0.0157)	0.0237 (0.4833)

Seasonal dummy variables' coefficients omitted.

Table 8
Estimates of the long-run elasticities of demand with respect to price, advertising and expenditure

Product	ϵ_{i1}	ϵ_{i2}	ϵ_{i3}	ϵ_{i4}	ϵ_{i5}	ϵ_{i6}	ϵ_{i7}	Expenditure elasticity, η_i
Compensated price elasticities, ϵ_{ij}								
(1) Beer	−0.405 (2.153)	0.122 (1.262)	−0.044 (0.456)	0.011 (0.126)	0.119 (0.707)	0.094 (0.672)	0.104 (0.663)	0.978 (4.839)
(2) Spirits	0.270 (1.262)	−1.363 (8.193)	−0.205 (1.289)	−0.149 (1.257)	0.844 (3.544)	−0.128 (0.637)	0.731 (3.433)	1.602 (5.672)
(3) Wine	−0.131 (0.456)	−0.273 (1.289)	−0.793 (2.391)	0.222 (0.995)	1.453 (3.538)	−1.573 (4.351)	1.094 (2.891)	0.712 (1.282)
(4) Tobacco	0.011 (0.126)	−0.065 (1.258)	0.073 (0.995)	−0.407 (4.278)	0.029 (0.222)	0.511 (4.203)	−0.152 (1.147)	0.403 (1.847)
(5) Food and soft drink	0.027 (0.707)	0.087 (3.544)	0.113 (3.538)	0.007 (0.222)	−0.121 (1.647)	0.091 (1.613)	−0.204 (3.649)	0.272 (3.293)
(6) Clothing and footwear	0.049 (0.672)	−0.030 (0.637)	−0.277 (4.351)	0.275 (4.203)	0.208 (1.613)	−0.386 (2.693)	0.162 (1.202)	0.876 (3.382)
(7) Other non-durables	0.022 (0.663)	0.070 (3.433)	0.078 (2.891)	−0.033 (1.147)	0.188 (3.649)	0.066 (1.202)	−0.014 (0.181)	1.821 (14.619)
	ϕ_{i1}	ϕ_{i2}	ϕ_{i3}	ϕ_{i4}	ϕ_{i5}	ϕ_{i6}	ϕ_{i7}	
Advertising elasticities, ϕ_{ij}								
(1) Beer	0.065 (2.294)	−0.050 (2.637)	−0.001 (0.061)	0.049 (2.010)	0.010 (0.260)	−0.048 (1.598)	−0.024 (0.465)	–
(2) Spirits	−0.016 (0.389)	0.002 (0.057)	0.041 (1.181)	−0.0004 (0.010)	−0.169 (2.854)	−0.035 (0.769)	0.179 (2.264)	–
(3) Wine	−0.035 (0.402)	−0.003 (0.046)	0.008 (0.116)	−0.141 (1.823)	−0.020 (0.159)	−0.246 (2.534)	0.436 (2.614)	–
(4) Tobacco	0.027 (0.772)	−0.014 (0.575)	−0.014 (0.494)	0.057 (1.846)	−0.038 (0.770)	0.106 (2.708)	−0.124 (1.852)	–
(5) Food and soft drink	−0.015 (1.117)	−0.008 (0.903)	0.021 (1.977)	0.002 (0.206)	−0.002 (0.104)	0.024 (1.672)	−0.024 (0.957)	–
(6) Clothing and footwear	−0.044 (1.056)	0.030 (1.071)	0.016 (0.441)	−0.061 (1.648)	−0.002 (0.039)	−0.086 (1.816)	0.102 (1.527)	–
(7) Other non-durables	0.016 (0.790)	0.008 (0.622)	−0.027 (1.601)	0.010 (0.551)	0.026 (0.924)	0.020 (0.909)	−0.014 (0.431)	–

Derived from long-run preference parameters estimated with homogeneity and symmetry imposed; see Tables 4 and 5. Elasticities evaluated at the sample mean values for the budget shares. Asymptotic t-ratios are given in parentheses.

Table 9
Estimates of the loading matrix ***D*** in the error-correction model

Product	Product					
	(1) Beer	(2) Spirits	(3) Wine	(4) Tobacco	(5) Food and soft drink	(6) Clothing and footwear
(1) Beer	−0.9152 (10.3147)	−0.1524 (1.0097)	−0.0926 (0.6165)	0.0352 (0.2714)	−0.0166 (0.3035)	0.0235 (0.3182)
(2) Spirits	−0.0172 (0.3120)	−0.9378 (9.9379)	0.2091 (2.2315)	0.0071 (0.0889)	0.0255 (0.7586)	−0.0357 (0.7726)
(3) Wine	0.0358 (0.7276)	0.0174 (0.2075)	−0.6679 (8.0024)	−0.1926 (2.7032)	0.0156 (0.5303)	0.0394 (0.9582)
(4) Tobacco	−0.1019 (1.7853)	−0.0141 (0.1452)	−0.1770 (1.8253)	−0.7230 (8.7802)	0.0303 (0.9010)	−0.1222 (2.5634)
(5) Food and soft drink	0.2541 (2.1301)	−0.1005 (0.4959)	−0.4407 (2.1785)	0.6343 (0.6788)	−0.7462 (10.3816)	0.4295 (4.2366)
(6) Clothing and footwear	−0.0869 (0.8579)	0.0349 (0.2022)	0.4648 (2.6980)	−0.3438 (2.3613)	−0.0455 (0.7898)	−0.5121 (6.1405)

Homogeneity and symmetry imposed. The *t*-ratios are given in parentheses.

attenuated. There appears to be only one significant own-advertising elasticity estimate (for beer). The rest are insignificantly different from zero, and three have the ‘wrong’ (negative) sign. Almost all cross-advertising effects are insignificantly different from zero. Where cross-advertising effects are significant, they may be spurious and implausible. For example, it is difficult to see why increased advertising on clothing and footwear should have a significant, depressing effect on wine consumption ($\phi_{36} = -0.246$) but raise tobacco consumption ($\phi_{46} = +0.106$), whilst having no (significant) effect on the consumption of anything else, including clothing and footwear itself (which, if anything, it appears to depress since $\phi_{66} < 0$). The point estimates of the own- and cross-advertising elasticities are, in general, also very small both in absolute terms and relative to the price and, especially, expenditure elasticities. There is very little evidence here to support the view that advertising is a potent force in the determination of consumer preferences and patterns of expenditure.

(vi) The estimated expenditure elasticity for spirits (+1.6) categorises that product as a ‘luxury’, which accords with previously published estimates (Duffy, 1991a). The expenditure elasticity for beer in Table 8 is close to unity, which is slightly higher than previous estimates. As a measure of long-run responsiveness, however, the beer expenditure elasticity may not be inconsistent with previous estimates if the latter, by reason of their model specifications, reflect short term effects. The expenditure elasticity of demand for wine is estimated to be 0.7: this point estimate is much lower than previous estimates which categorise wine as a ‘luxury’. This wine elasticity is imprecisely estimated, however, and with a standard error of 0.55, the population elasticity may exceed unity and lie close to previous estimates. The tobacco expenditure elasticity (0.4) is lower than, but not too far from, previous estimates: Treasury (1980), for example, reports a figure of 0.6. As one would expect, the expenditure elasticity of demand for food is low, and the estimate of 0.3 is similar to other estimates: Tiffin and Tiffin (1999) estimate this elasticity to be approximately 0.5.The expenditure elasticity of demand for clothing and footwear at 0.88 is slightly higher than previous estimates but still below unity, which is appropriate for a group of products that are generally regarded as ‘necessities’.

(vii) All of the elements on the leading diagonal of the loading matrix $\boldsymbol{D}$ in Table 9 are significantly different from zero and negative, which ensures that budget shares adjust to close any gaps in the previous period between actual and preferred budget shares.[9] Only a small number of the off-diagonal terms in $\boldsymbol{D}$ are significantly different from zero, so the evidence for inter-relatedness between markets in the dynamic process is sparse. This finding, taken in conjunction with the limited number of significant elements in the matrix $\boldsymbol{A}_0$ of short-term responses to changes in the explanatory variables in the system (see (ii) above) indicates that a simpler, more parsimonious specification for dynamics in the demand system may be obtained by careful ‘testing down’ and exclusion of insignificant terms. To do this properly would require an exhaustive testing procedure since there is no natural ordering of the hypotheses (which are conditional on each other in an interdependent demand system). This is an exercise that is managed more easily and effectively in a relatively small system. It is not attempted in the present large-scale project, but that is not to say that it is infeasible or that it is not worth considering in future research.

5. Conclusion

This paper has been concerned with testing for the influence of advertising on the inter-product distribution of consumer demand for non-durable goods and services in the UK, 1963–1996. Total demand for non-durables is disaggregated into seven product categories, and the long-run demand for those

[9] Additional evidence of cointegration could be sought by subjecting the residuals from the estimated long run demand system $\boldsymbol{w}_t = \boldsymbol{\Pi x}_t + \boldsymbol{e}_t$ to stationarity tests. However, the distribution of the corresponding test statistics depends on the number of explanatory variables in the model, and tables of critical values have not yet been published which accommodate as many variables as are used in this study.

products is modelled using an advertising-augmented version of the AIDS. Short-run dynamic adjustments to long-run equilibrium positions are modelled via a first-order error-correction model, which separates short-run from long-run behaviour and allows the matrix of long-run preference parameters to be estimated directly. Results indicate that the restrictions of price homogeneity and symmetry are consistent with the data. Estimates of the various types of demand elasticity are in general plausible, and confirm the strong influence of prices on the allocation of consumer expenditure. There is little support for the hypothesis that advertising has the power to effect marked changes in the inter-product pattern of consumer demand.

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